Classifying the Ripeness of Mangoes Using Image Processing and Deep Learning

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Introduction

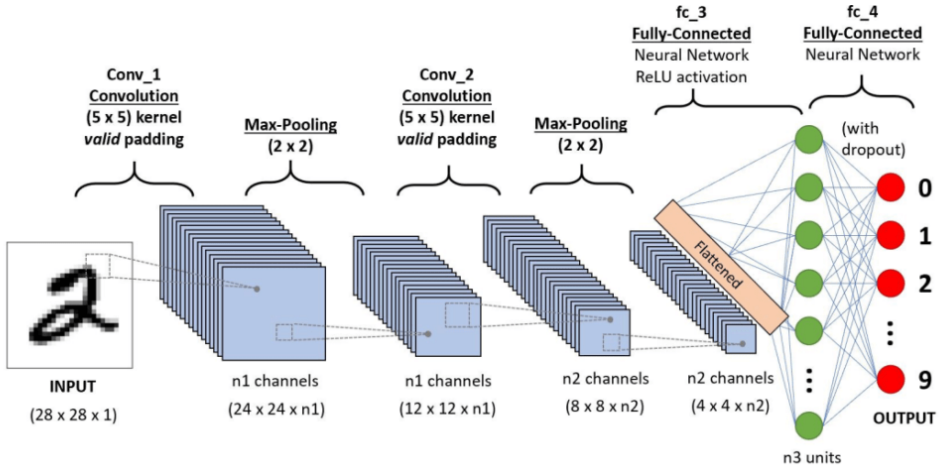
Economic Importance of Mangoes in Thailand

Mangoes are a crucial agricultural product in Thailand's economy. Thailand ranks as the world’s third-largest mango producer, with approximately 3,152 square kilometers dedicated to mango cultivation and an annual yield of about 3.12 million tons. This extensive production positions mangoes as an essential crop contributing significantly to both the agricultural sector and national revenue.

Introduction

Research Objective

The objective of this research is to develop an advanced mango sorting system capable of accurately identifying ripeness levels through the use of image processing and deep learning techniques. This approach leverages deep learning's ability to learn and recognize specific visual characteristics, such as color and texture changes, associated with different ripeness stages across mango varieties. The system is designed to enhance sorting efficiency, ensuring consistency and accuracy in distinguishing ripeness stages.



In this study, we focus on classifying two popular mango varieties, Okrong and Mahachanok, each exhibiting unique visual traits that evolve through their ripening process. By specifically targeting these two varieties, the system is optimized to handle the subtle differences in texture and color unique to each, thereby improving the precision of automated sorting for export-quality standards.

RESEARCH BACKGROUND

S. Jirapattarasakul, S. Thanyacharoen, and T. Yingthawornsuk emphasize the importance of mangoes as both a staple food and a significant export for Thailand. As one of the world's leading mango exporters, Thailand relies on mango cultivation as a vital component of its agricultural economy.

T. Yingthawornsuk highlighted advancements in Deep Learning and image processing technologies that enhance the efficiency of fruit sorting, including for mangoes. These techniques enable precise detection and classification of unique features that indicate ripeness levels, greatly improving sorting accuracy and consistency.

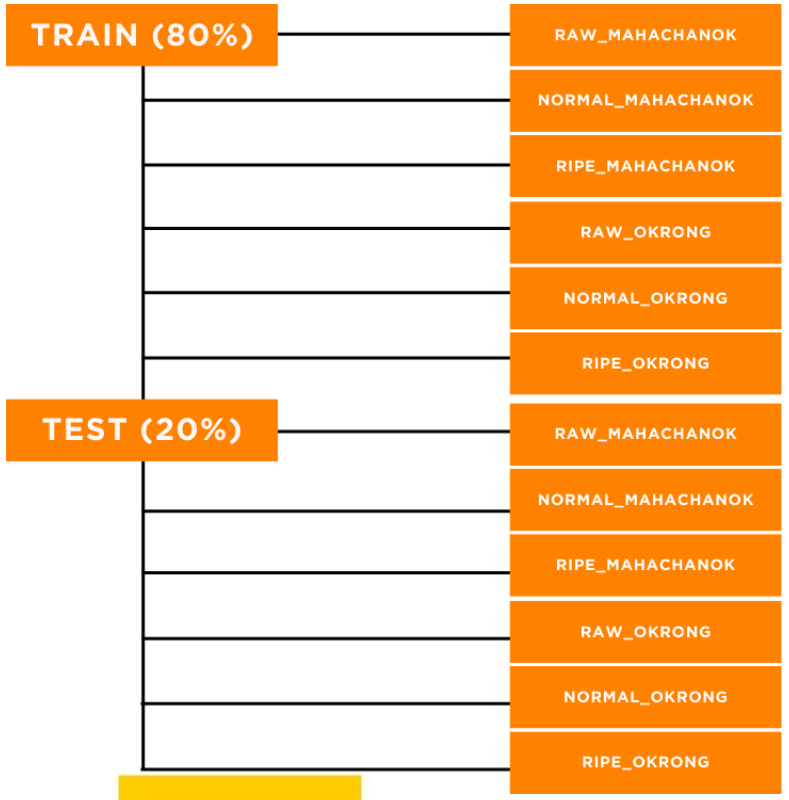
This research highlights the effective use of Deep Learning to sort Mahachanok and Okrong mango varieties by ripeness, accurately identifying the unique features of each type. This automated system enhances efficiency and consistency in sorting, minimizing manual labor needs while maintaining high product quality. Such advancements demonstrate the potential for industrial-scale automated sorting, enabling Thai mangoes to meet export standards more reliably and boosting competitiveness in the global market.

Materials and Methods

Training and Testing Data Folder

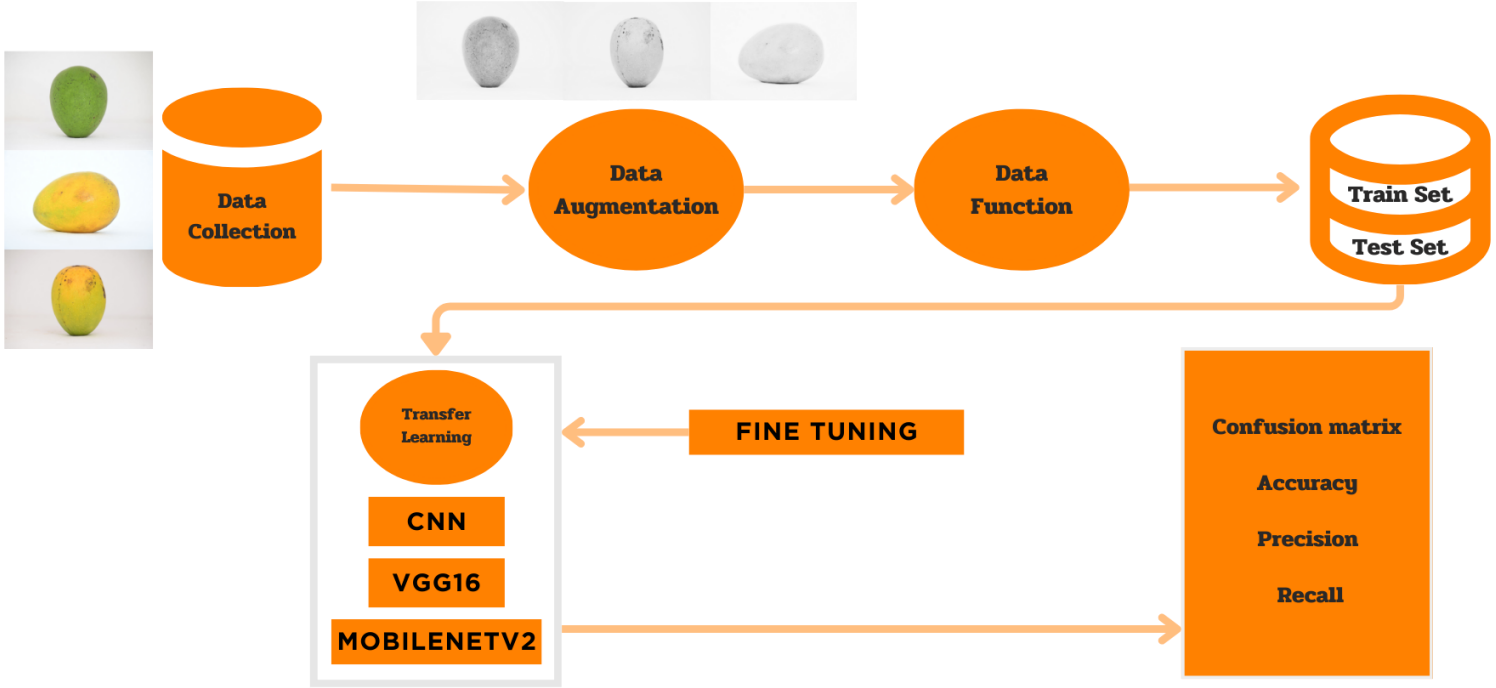
The models were trained to classify both mango varieties and ripeness stages using three prominent architectures, as detailed below:

- VGG16 (Visual Geometry Group 16-layer model)
- MobileNetV2 (Mobile Network Version 2)
- CNN1D (One-Dimensional Convolutional Neural Network)



Materials and Methods

Proposed Methodology



Materials and Methods

Performance Metric

In this research, classification prediction performance was evaluated using a Confusion Matrix. Key metrics included Accuracy (Equation 1), Precision (Equation 2), Recall (Equation 3), and F1-Score (Equation 4). Each of these metrics provides a distinct insight into the model's predictive capabilities, ensuring a comprehensive assessment of its effectiveness in distinguishing mango ripeness stages and varieties.

$$\text{Accuracy} = \frac{TP + TN}{TP+TN+FP+FN}$$

$$\text{Recall} = \frac{TP + TN}{TP+TN+FP+FN}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{F1-Score} = 2\,\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Materials and Methods

Fine Tuning

Evaluation of Average Versus Maximum Values

Optimizer	Maximum	Average
Accuracy	1.00	0.99

Optimize Learning Rate

Optimizer	Learning rate = 0.001	Learning rate = 0.0001
Accuracy	0.99	0.96

Materials and Methods

Fine Tuning

During the Fine Tuning phase, the highest model accuracy achieved was 1.00, with an average accuracy of 0.99 for the VGG16 model. The optimal learning rate for testing preparation was found to be 0.001, achieving an accuracy of 0.99. In comparison, a learning rate of 0.0001 resulted in a lower accuracy of 0.90. This demonstrates the significant impact of selecting an appropriate learning rate on model performance.

To optimize testing preparation, the research team selected the following parameters: -A learning rate of 0.001 -A batch size of 16

Materials and Methods

Add libraries

In this phase, essential libraries were integrated to support the testing process. The libraries used include

- L2 Dropout
- K-fold Early
- stopping

In this experiment, three classification tasks were conducted as follows

Classification of mango varieties and ripeness levels for both Mahachanok and Okrong mangoes. Ripeness classification exclusively for the Mahachanok mango variety. Ripeness classification exclusively for the Okrong mango variety.

Results and Discussion

Mahachanok and Okrong mangoes

• **VGG16** demonstrated the highest performance with 98% accuracy, alongside precision, recall, and F1-score of 0.98, significantly outperforming MobileNetV2 at 91% and CNN at 86%. This highlights VGG16's ability to effectively identify ripeness levels in mangoes.

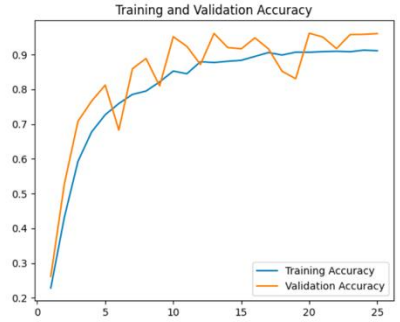
• However, subtle differences in skin color and texture, particularly between semi-ripe and fully ripe stages, posed challenges, leading to occasional misclassification when features were not distinct enough.

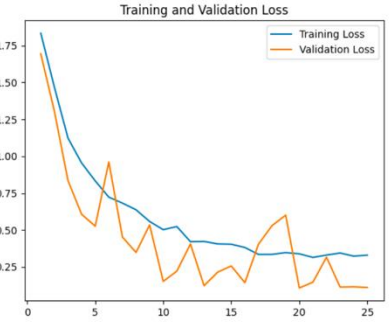
• Overall, VGG16 is the most effective model for classifying the ripeness of mango varieties using Deep Learning, offering superior consistency and accuracy, which are crucial for automated mango sorting systems.

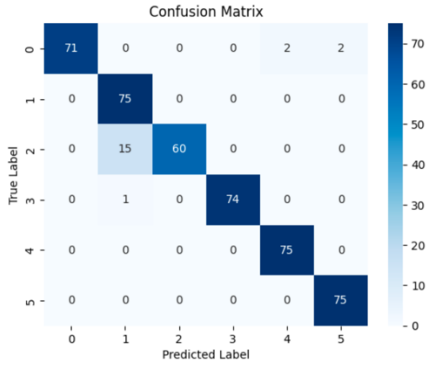
Results and Discussion

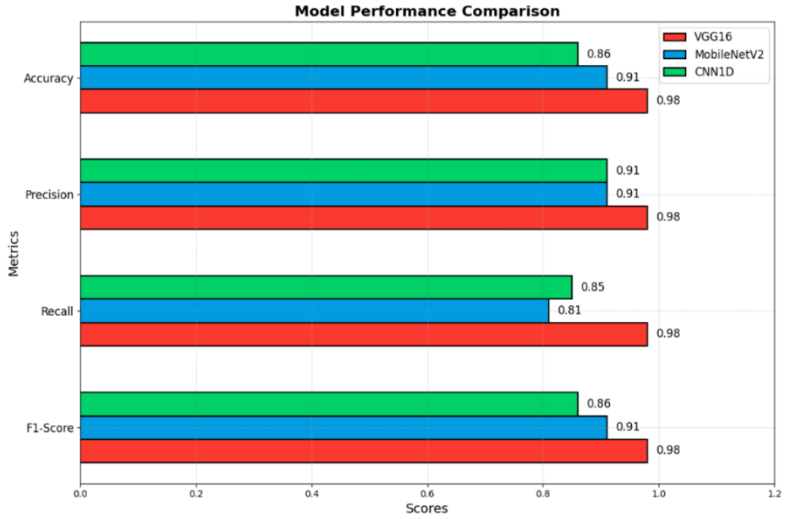
Mahachanok and Okrong mangoes

Performance of the VGG16 Model:
For both Mhachanok and Okrong mangoes, the VGG16 model achieved a peak accuracy of 98%.









Results and Discussion

Mahachanok mangoes

• **VGG16** demonstrated the highest performance in classifying mango ripeness levels, achieving accuracy, precision, recall, and F1-score of 0.99, significantly outperforming MobileNetV2 (0.97) and CNN (0.96). This establishes VGG16 as the most effective model for handling the task using Deep Learning techniques.

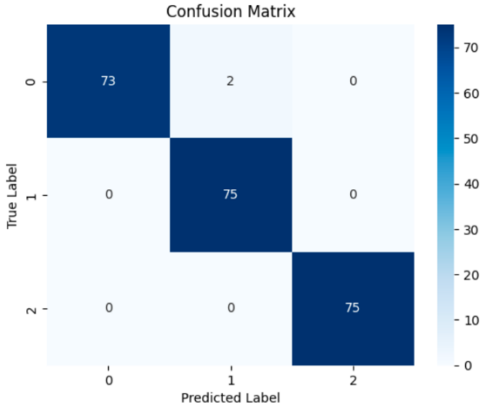
• The model's robustness highlights its ability to consistently identify ripeness levels in mangoes, though gradual transitions in skin color and texture between semi-ripe and fully ripe stages occasionally led to misclassification due to overlapping visual characteristics.

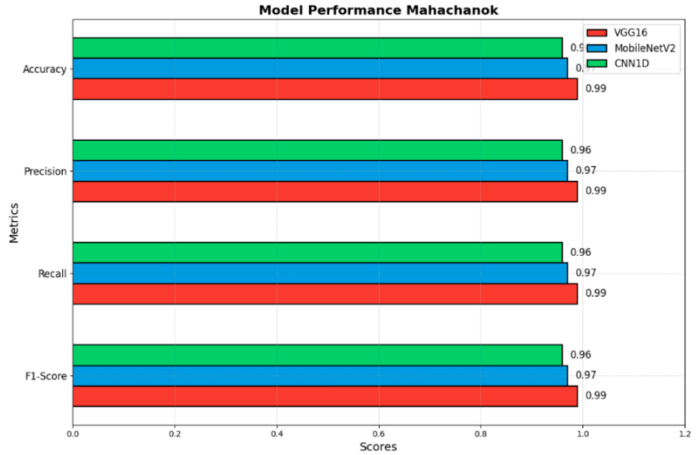
• These findings underscore the potential of VGG16 in industrial-scale automated mango sorting systems, offering enhanced precision and consistency to meet export-quality standards and reduce dependency on manual labor.

Results and Discussion

Mahachanok mangoes

Performance of the VGG16 Model:
For the Mahachanok mango variety, the VGG16 model achieved a maximum accuracy of 99.11%.





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Results and Discussion

Okrong mangoes

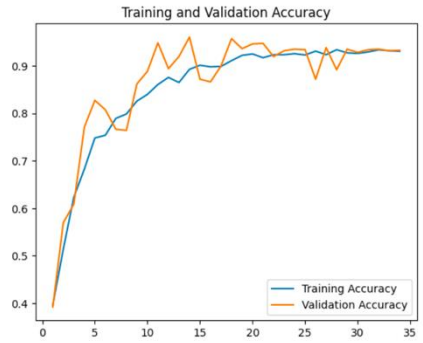
• **VGG16** demonstrated superior performance in classifying mango ripeness levels, achieving the highest scores across all metrics, including accuracy, precision, recall, and F1-score at 0.99. This performance surpassed MobileNetV2 (0.98) and CNN (0.96), establishing VGG16 as the most reliable and effective model for the task.

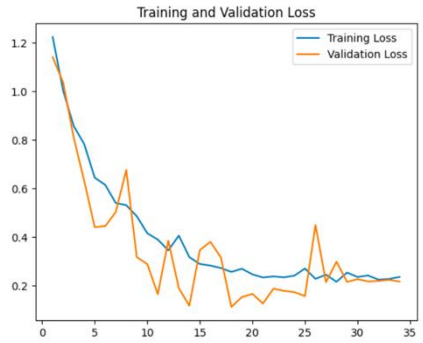
• Its ability to consistently and accurately classify mango ripeness makes it a valuable tool for automated sorting systems, highlighting its potential to enhance efficiency and reduce errors in industrial applications. These findings reinforce the significance of Deep Learning in advancing agricultural technologies.

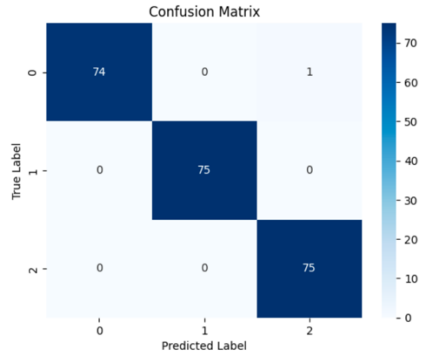
Results and Discussion

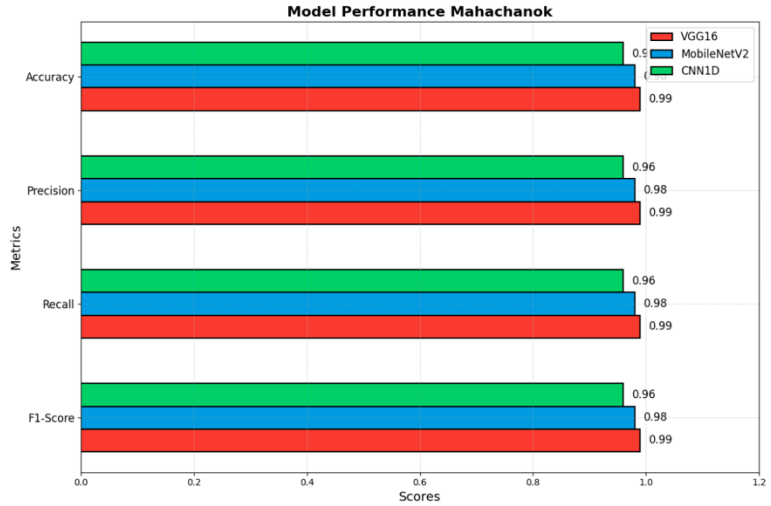
Okrong mangoes

Performance of the VGG16 Model:
For the Okrong mango variety, the VGG16 model achieved a maximum accuracy of 99.60%.









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Conclusion and Future Work

Conclusion

The research results highlight that the VGG16 model demonstrates the highest performance in classifying mango ripeness, particularly when distinguishing specific characteristics of the Mahachanok and Okrong varieties. Due to its deep architecture, VGG16 effectively captures subtle changes in color and texture that indicate different ripeness stages, making it the most suitable model for developing an automated mango sorting system. This capability supports efficient, consistent classification and addresses the limitations of manual sorting processes, which are often inconsistent and error-prone.

Integrating VGG16 into automated sorting not only improves accuracy but also aligns the sorting process with international quality standards a critical requirement for export markets. This automated system can enhance productivity, reduce labor dependency, and ultimately increase the value of Thai mangoes in global markets, strengthening their competitiveness.

Overall, the study underscores the potential of Deep Learning in agricultural applications. It establishes a foundation for future research into similar classification tasks for other fruits requiring high-resolution sorting or further advancements such as real-time image processing. This approach could lead to faster, more adaptive sorting solutions that meet real-world demands.

Conclusion and Future Work

Future Work

This research holds significant potential to extend Deep Learning applications to other fruits, specifically grapes used in wine production, where precise ripeness classification is essential for achieving high-quality wine. With VGG16's capability to detect subtle characteristics like color and texture changes, the model could be effectively adapted for sorting grapes, particularly in processes requiring consistency and accuracy.

Accurate sorting of grapes by ripeness is critical, as ripeness levels directly impact the flavor and quality of wine. By implementing an automated sorting system powered by Deep Learning, such as VGG16, the wine production process could be greatly enhanced, increasing both accuracy and efficiency. Furthermore, this approach would ensure consistent grape quality, aligning with international wine production standards.

In conclusion, expanding this research to include grape sorting represents an evolution in applying Deep Learning to the wine industry, supporting higher precision in the sorting process and ultimately enhancing wine quality.

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